

PAPER • OPEN ACCESS

Identification of induction motor parameters with measurement errors

To cite this article: D V Ivanov *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **560** 012163

View the [article online](#) for updates and enhancements.



IOP | ebooks™

Bringing you innovative digital publishing with leading voices to create your essential collection of books in STEM research.

Start exploring the **collection** - download the first chapter of every title for free.

Identification of induction motor parameters with measurement errors

D V Ivanov¹, E A Sandler¹, N V Chertykovtseva¹, E A Tikhomirov² and N S Semenova³

¹Samara State University of Transport, 2v, Svobody ave., Samara, 443066, Russia

²Bauman Moscow State Technical University, 5, 2 Baumanskaya ave., Moscow, 105005, Russia

³Moscow State University of Technologies and Management, 73, Zemlyanoj val ave., Moscow, 109004, Russia

E-mail: dvi85@list.ru

Abstract. This paper proposes an algorithm for estimating parameters of asynchronous traction motors in the presence of measurement errors. The presence of measurement errors of voltage and current leads to biased estimates of motor parameters. Algorithmic approach to eliminating the influence of noise is used most often as it increases the accuracy of estimates without precision current and voltage meters. Known modifications of algorithms based on the method of total least squares suggest filtering the derivatives of noise, which increases the complexity of the algorithm and also changes the statistical properties of noise. The proposed algorithm is a generalization of the total least-squares technique and does not require knowledge of the laws governing the distribution of measurement errors. The results of modeling show that the parameter estimation is highly accurate than the ordinary least square. The proposed algorithm can be used to create precision control systems, as well as to diagnose faults in electric motors by K parameters.

1. Introduction

Asynchronous traction motors are widely applied in industry and vehicles. The primary advantages of these motors are their simple design, reliability, and comparatively low prices and maintenance costs. High-quality asynchronous motors available today offer performance comparable to DC motors [1].

To operate asynchronous motors efficiently, one needs to precisely know the parameters of the motor as an object (here, parameters mean the aggregate parameters of the asynchronous motor's equivalent circuit). This information can usually be found in the datasheet for the motor in question, but actual values may differ from those in the datasheet. Besides, under operating conditions a 50 % change is possible in the active stator and rotor resistance as well as a 10 % increase in mutual induction, while the change in leakage inductance may be up to 20 %.

Because of this, various methods are used to identify parameters for the asynchronous motor's equivalent circuit.

One of the most widespread methods is the ordinary-least-squares technique [2]. But that technique yields biased parameter estimates if the input signal is noisy. Motor noise may result from electromagnetic noise and measurement errors. As a result, the least-squares technique requires using precision instruments protected from noise, but that is quite difficult in practice and makes



asynchronous motors more expensive.

Paper [3] proposes estimation with the generalized-total-least-squares technique to identify motor parameters from noisy observations. References [4–6] propose recursive algorithms to identify K parameters for the motor with the total-least-squares technique. These references propose filtering out noise in the first and second current and voltage derivatives. But derivative filtration does not always reduce interference to negligible values; and when running through filters, white noise becomes colored.

This paper proposes an algorithm for identifying K parameters that allows unbiased estimates to be obtained as part of measuring noisy derivatives.

2. Problem statement

There are generally known assumptions, the mathematical model for the asynchronous traction motor can be expressed in the fixed coordinates $(\alpha, \beta, 0)$ as follows:

$$\frac{di^{(s\alpha)}}{dt} = \frac{1}{\sigma L_s} U^{(s\alpha)} - \gamma i^{(s\alpha)} + \frac{\beta}{T_r} \Psi^{(r\alpha)} + p\beta\omega \Psi^{(r\beta)}, \quad (1)$$

$$\frac{di^{(s\beta)}}{dt} = \frac{1}{\sigma L_s} U^{(s\beta)} - \gamma i^{(s\beta)} + \frac{\beta}{T_r} \Psi^{(r\beta)} + p\beta\omega \Psi^{(r\alpha)}, \quad (2)$$

$$\frac{d\Psi^{(s\alpha)}}{dt} = \frac{L_m}{T_r} i^{(s\alpha)} - \frac{\Psi^{(r\alpha)}}{T_r} - p\omega \Psi^{(r\beta)}, \quad (3)$$

$$\frac{d\Psi^{(s\beta)}}{dt} = \frac{L_m}{T_r} i^{(s\beta)} - \frac{\Psi^{(r\alpha)}}{T_r} - p\omega \Psi^{(r\alpha)}, \quad (4)$$

$$M = \frac{3}{2} p \frac{L_m}{\sigma L_r} (\Psi^{(r\alpha)} i^{(s\beta)} - \Psi^{(r\beta)} i^{(s\alpha)}), \quad (5)$$

$$\frac{d\omega}{dt} = \frac{p}{J} (M - M_c), \quad (6)$$

where $i^{(s\alpha)}$ and $i^{(s\beta)}$ are projections of stator current on the axes α and β , respectively; $U^{(s\alpha)}$ and $U^{(s\beta)}$ are projections of stator voltage on the axes α and β , respectively; $\Psi^{(r\alpha)}$ and $\Psi^{(r\beta)}$ are projections of rotor flux linkages on the axes α and β , respectively; $\sigma = 1 - L_m^2 / (L_s L_r)$ is a total dispersion coefficient; L_m , L_s , and L_r are mutual induction, stator induction, and rotor induction, respectively; R_s and R_r represent active stator and rotor resistance; T_r is the time constant for the rotor; p is the number of pole pairs; ω is the rotor rotation speed; J is the equivalent moment of inertia for the motor; M is an electromagnetic moment; M_c is a motion resistance moment; and γ and β are certain coefficients that depend on the induction and active resistance of the motor.

It is noteworthy that the equation parameters are dependent, and to unequivocally identify the asynchronous motor, one only needs to determine R_s , L_s , σ , and T_r .

The identification of parameters requires excluding the unmeasurable projections of rotor flux linkages from the equations. Assuming that $\frac{d\omega}{dt} = 0$ after the transformations, we obtain [5]:

$$-\left(\frac{d^2 i^{(s\alpha)}}{dt^2} + p\omega \frac{di^{(s\beta)}}{dt}\right) = K_1 \frac{di^{(s\alpha)}}{dt} + K_2 i^{(s\alpha)} + K_3 p\omega i^{(s\beta)} - K_4 \left(\frac{dU^{(s\alpha)}}{dt} + p\omega U^{(s\beta)}\right) - K_5 U^{(s\alpha)}, \quad (7)$$

$$-\frac{d^2 i^{(s\beta)}}{dt^2} + p\omega \frac{di^{(s\alpha)}}{dt} = K_1 \frac{di^{(s\beta)}}{dt} + K_2 i^{(s\beta)} + K_3 p\omega i^{(s\alpha)} - K_4 \left(\frac{dU^{(s\beta)}}{dt} + p\omega U^{(s\alpha)}\right) - K_5 U^{(s\beta)}. \quad (8)$$

Using coefficients K_1 , K_2 , K_3 , K_4 , and K_5 , one can find R_s , L_s , σ and T_r :

$$T_r = \frac{K_4}{K_5}, R_s = \frac{K_3}{K_4}, L_s = \frac{K_1 - K_3}{K_5}, \sigma = \frac{K_5}{K_4(K_1 - K_3)}.$$

As the parameters are identified digitally, it is convenient to move from differential equations to difference equations.

Let us consider determining K parameters with equation (7). Let us approximate the first and second derivatives with discrete differences:

$$\frac{di}{dt} \approx \frac{1}{\Delta}(i_k - i_{k-1}), \quad \frac{d^2i}{dt^2} \approx \frac{1}{\Delta^2}(i_k - 2i_{k-1} + i_{k-2}), \quad \frac{dU}{dt} \approx \frac{1}{\Delta}(U_k - U_{k-1}),$$

where Δ is a sampling interval.

Then the equation takes the form:

$$\begin{aligned} -\left(\frac{1}{\Delta^2}(i_k^{(s\alpha)} - 2i_{k-1}^{(s\alpha)} + i_{k-2}^{(s\alpha)}) + \frac{p\omega}{\Delta}(i_k^{(s\beta)} - i_{k-1}^{(s\beta)})\right) &= K_1 \frac{1}{\Delta}(i_k^{(s\alpha)} - i_{k-1}^{(s\alpha)}) + K_2 i_k^{(s\alpha)} + K_3 p\omega i_k^{(s\beta)} - \\ &- K_4 \left(\frac{1}{\Delta}(U_k^{(s\alpha)} - U_{k-1}^{(s\alpha)}) + p\omega U_k^{(s\beta)}\right) - K_5 U_k^{(s\alpha)}. \end{aligned} \quad (9)$$

Let us note that in identification systems, voltage and current values are measured with error; that is,

$$\tilde{i}_k^{(s\alpha)} = i_k^{(s\alpha)} + \xi_k^{(is\alpha)}, \quad \tilde{i}_k^{(s\beta)} = i_k^{(s\beta)} + \xi_k^{(is\beta)}, \quad \tilde{U}_k^{(s\alpha)} = U_k^{(s\alpha)} + \xi_k^{(Us\alpha)}, \quad \tilde{U}_k^{(s\beta)} = U_k^{(s\beta)} + \xi_k^{(Us\beta)}, \quad (10)$$

where $i_k^{(s\alpha)}$ and $i_k^{(s\beta)}$ are nonobservable values for stator-current projections on the axes α and β , respectively; $\tilde{i}_k^{(s\alpha)}$ and $\tilde{i}_k^{(s\beta)}$ are observable values for stator-current projections on the axes α and β , respectively; $U_k^{(s\alpha)}$ and $U_k^{(s\beta)}$ are nonobservable values for stator-voltage projections on the axes α and β , respectively; $\tilde{U}_k^{(s\alpha)}$ and $\tilde{U}_k^{(s\beta)}$ are observable values for stator-voltage projections on the axes α and β , respectively; and $\xi_k^{(is\alpha)}$, $\xi_k^{(is\beta)}$, $\xi_k^{(Us\alpha)}$, and $\xi_k^{(Us\beta)}$ are measurement errors for the corresponding values.

Thus, the problem of identifying parameters can be formulated as one of finding coefficient estimates for K_1, K_2, K_3, K_4 , and K_5 in equation (9) according to noisy observations (10).

3. Identification criterion

Let us assume that the following conditions are satisfied:

1. $\xi_k^{(is\alpha)}$, $\xi_k^{(is\beta)}$, $\xi_k^{(Us\alpha)}$, and $\xi_k^{(Us\beta)}$ are independent sequences with $E(\xi_k^{(is\alpha)}) = E(\xi_k^{(is\beta)}) = E(\xi_k^{(Us\alpha)}) = E(\xi_k^{(Us\beta)}) = 0$, where E is an expectation operator;
2. $E((\xi_k^{(is\alpha)})^2) = \sigma_{is\alpha}^2$, $E((\xi_k^{(is\beta)})^2) = \sigma_{is\beta}^2$, $E((\xi_k^{(Us\alpha)})^2) = \sigma_{Us\alpha}^2$, $E((\xi_k^{(Us\beta)})^2) = \sigma_{Us\beta}^2$.
3. $\xi_k^{(is\alpha)}$, $\xi_k^{(is\beta)}$, $\xi_k^{(Us\alpha)}$, and $\xi_k^{(Us\beta)}$ are independent in the aggregate.
4. The covariance matrix H is positive definite:

$$E(\varphi_k^{(0)}(\varphi_k^{(0)})^T) = H,$$

where

$$\varphi_k^{(0)} = \begin{pmatrix} \frac{1}{\Delta}(i_k^{(s\alpha)} - i_{k-1}^{(s\alpha)}) & i_k^{(s\alpha)} & p\omega i_k^{(s\beta)} & -\left(\frac{1}{\Delta}(U_k^{(s\alpha)} - U_{k-1}^{(s\alpha)}) + p\omega U_k^{(s\beta)}\right) & -U_k^{(s\alpha)} \end{pmatrix}^T.$$

Assumption 4 is satisfied if the motor is in a transient process; with constant or sine signals, assumption 4 is not satisfied.

The generalized error will be given by:

$$\begin{aligned} \varepsilon_k = & -\left(\frac{1}{\Delta^2}(\xi_k^{(is\alpha)} - 2\xi_{k-1}^{(is\alpha)} + \xi_{k-2}^{(is\alpha)}) + \frac{p\omega}{\Delta}(\xi_k^{(is\beta)} - \xi_{k-1}^{(is\beta)})\right) - K_1 \frac{1}{\Delta}(\xi_k^{(is\alpha)} - \xi_{k-1}^{(is\alpha)}) - K_2 \xi_k^{(is\alpha)} - K_3 p\omega \xi_k^{(s\beta)} - \\ & + K_4 \left(\frac{1}{\Delta}(\xi_k^{(Us\alpha)} - \xi_{k-1}^{(Us\alpha)}) + p\omega \xi_k^{(s\beta)}\right) + K_5 U_k^{(s\alpha)}. \end{aligned}$$

Using assumptions 1 through 4, we can show that $E(\varepsilon_k) = 0$.

Let us introduce the following designations:

$$\begin{aligned} K = & (K_1 \quad K_2 \quad K_3 \quad K_4 \quad K_5)^T, \\ \varphi_k = & \left(\frac{1}{\Delta}(\tilde{i}_k^{(s\alpha)} - \tilde{i}_{k-1}^{(s\alpha)}) \quad \tilde{i}_k^{(s\alpha)} \quad p\omega \tilde{i}_k^{(s\beta)} \quad -\left(\frac{1}{\Delta}(\tilde{U}_k^{(s\alpha)} - \tilde{U}_{k-1}^{(s\alpha)}) + p\omega \tilde{U}_k^{(s\beta)}\right) \quad -\tilde{U}_k^{(s\alpha)} \right)^T \\ \varphi_k^{(\xi)} = & \left(\frac{1}{\Delta}(\xi_k^{(is\alpha)} - \xi_{k-1}^{(is\alpha)}) \quad \xi_k^{(is\alpha)} \quad p\omega \xi_k^{(is\beta)} \quad -\left(\frac{1}{\Delta}(\xi_k^{(Us\alpha)} - \xi_{k-1}^{(Us\alpha)}) + p\omega \xi_k^{(Us\beta)}\right) \quad -\xi_k^{(Us\alpha)} \right)^T, \\ y_k = & -\left(\frac{1}{\Delta^2}(\tilde{i}_k^{(s\alpha)} - 2\tilde{i}_{k-1}^{(s\alpha)} + \tilde{i}_{k-2}^{(s\alpha)}) + \frac{p\omega}{\Delta}(\tilde{i}_k^{(s\beta)} - \tilde{i}_{k-1}^{(s\beta)})\right). \end{aligned}$$

The dispersion of the generalized error will be given by:

$$\begin{aligned} E(\varepsilon_k^2) = & E\left(-\left(\frac{1}{\Delta^2}(\xi_k^{(is\alpha)} - 2\xi_{k-1}^{(is\alpha)} + \xi_{k-2}^{(is\alpha)}) + \frac{p\omega}{\Delta}(\xi_k^{(is\beta)} - \xi_{k-1}^{(is\beta)})\right) - K^T \varphi_k^{(\xi)}\right)^2 = \\ = & \left(\frac{6 \cdot \sigma_{is\alpha}^2}{\Delta^4} + \frac{2p^2 \omega^2 \sigma_{is\beta}^2}{\Delta^2}\right) + K^T H_\xi K + 2K^T \tilde{h}_\xi, \end{aligned}$$

where

$$\begin{aligned} \tilde{h}_\xi = & E\left(\varphi_k^{(\xi)} \left(\frac{1}{\Delta^2}(\xi_k^{(is\alpha)} - 2\xi_{k-1}^{(is\alpha)} + \xi_{k-2}^{(is\alpha)}) + \frac{p\omega}{\Delta}(\xi_k^{(is\beta)} - \xi_{k-1}^{(is\beta)})\right)\right) = \begin{pmatrix} \frac{3\sigma_{is\alpha}^2}{\Delta^3} & \frac{\sigma_{is\alpha}^2}{\Delta^2} & \frac{p^2 \omega^2 \sigma_{is\beta}^2}{\Delta} & 0 & 0 \end{pmatrix}^T, \\ H_\xi = & E\left(\varphi_k^{(\xi)} (\varphi_k^{(\xi)})^T\right) = \begin{pmatrix} \frac{2\sigma_{is\alpha}^2}{\Delta^2} & \frac{\sigma_{is\alpha}^2}{\Delta} & 0 & 0 & 0 \\ \frac{\sigma_{is\alpha}^2}{\Delta} & \sigma_{is\alpha}^2 & 0 & 0 & 0 \\ 0 & 0 & p^2 \omega^2 \sigma_{is\beta}^2 & 0 & 0 \\ 0 & 0 & 0 & \frac{2\sigma_{Us\alpha}^2}{\Delta^2} + p^2 \omega^2 \sigma_{Us\beta}^2 & \frac{\sigma_{Us\alpha}^2}{\Delta} \\ 0 & 0 & 0 & \frac{\sigma_{Us\alpha}^2}{\Delta} & \sigma_{Us\alpha}^2 \end{pmatrix}. \end{aligned}$$

We will find an estimate for the vector of parameters K from the minimum condition of the weighted sum of squared errors :

$$\min_K \frac{\sum_{k=1}^N (y_k - K^T \varphi_k)^2}{\left(\frac{6 \cdot \sigma_{is\alpha}^2}{\Delta^4} + \frac{2p^2 \omega^2 \sigma_{is\beta}^2}{\Delta^2}\right) + K^T H_\xi K + 2K^T \tilde{h}_\xi} \quad (11)$$

Criterion (11) is a generalized Rayleigh ratio. Algorithms for minimizing generalized Rayleigh ratios can be found in [7,8].

4. Simulation results

The algorithm based on criterion (11) was compared with the least-squares technique. It was assumed that currents and voltages were measured with noise. Noise was modeled by using independent Gaussian random variables with zero mean.

The true values of K parameters are:

$$K_1 = 192, K_2 = 1542, K_3 = 134, K_4 = 40, \text{ and } K_5 = 277.$$

We used the relative mean-square error of parameter estimation as a quality indicator for the model:

$$\delta K_m = \sqrt{\frac{\|\hat{K}_m - K_m\|^2}{\|K_m\|^2}} \cdot 100\%.$$

Table 1. Parameter estimation errors.

K_m	δK_m for LS (%)	δK_m for criterion (11) (%)
K_1	0.29	0.21
K_2	33.5	10.1
K_3	0.42	0.22
K_4	0.22	0.14
K_5	0.33	0.20

5. Conclusion

This paper proposed a criterion for identifying K parameters for the asynchronous traction motor in the presence of measurement errors. Further research will focus on creating recurrent algorithms for identifying asynchronous motors in the presence of errors in variables and developing algorithms for identifying various classes of correlated noises [9].

References

- [1] Bose B K 2006 *Power Electronics And Motor Drives: Advances and Trends* (Academic Press) p 936
- [2] Stephan J and Bodson M 1994 Real-time estimation of the parameters and fluxes of induction motors *IEEE Transactions on Industry Electronics* **30(3)** 746–759
- [3] Moons C and De Moor B 1995 Parameter identification of induction motor drives *Automatica* **31(8)** 1137–47
- [4] Cirrincione M, Cirrincione G, Pucci M and Jaafari A 2010 The estimation of the induction motor parameters by the GeTLS EXIN neuron *2010 IEEE Energy Conversion Congress and Exposition* 1680–85
- [5] Cirrincione M, Pucci M and Vitale G 2012 *Power Converters and AC Electrical Drives with Linear Neural Networks* (Boca Raton: CRC Press, Taylor & Francis Group) p 661
- [6] Cirrincione G and Cirrincione M 2010 *Neural Based Orthogonal Data Fitting: The EXIN Neural Networks Series: Adaptive and Learning Systems for Signal Processing, Communications and Control* (New York: Wiley & Sons) p 255
- [7] Ivanov D V and Ivanov A V 2017 Identification fractional linear dynamic systems with fractional errors-in-variables *J. Phys.: Conf. Ser.* **803(1)** 012058
- [8] Ivanov D V 2013 Identification discrete fractional order linear dynamic systems with output error *Proc. Int. Siberian Conf. on Control and Communications (SIBCON'2013)* 14022145
- [9] Söderström T 2011 A generalized instrumental variable method for errors-in-variables *Automatica* **47(8)** 1656–66